Noise measurements around a first-order metal-insulator transition

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ABSTRACT

In this project conductance fluctuations is studied using power spectral density for a first order phase transition of V_2O_3 which occurs at around 150 /k while cooling. The technique involves study of the linear regression parameter α of the power spectrum to understand the noise parameters.

Contents

Chapter 1

Background Theory

1.1 Low frequency conductance fluctuations

Low frequency conductance fluctuation is a valuable tool to study low frequency fluctuations in condensed matter systems.Conductance fluctuations in a current carrying solid often show a pattern $S_v(f) \propto 1/f^{\alpha}$. This is usually refereed to as $1/f$ noise. Different statistical quantities can be calculated from the time series data. Power spectral density is the most common and powerful way to express the noise.

1.2 Power spectral density

Energy spectral density describes how the energy of the time series signal is distributed with frequency. Energy density of a time series data $x(t)$ is defined as

$$E = \int_{-\infty}^{+\infty} |x(t)|^2 dt \tag{1.1}$$

Fourier transform of the time series is given as

$$x_a = \int_{-\infty}^{\infty} e^{-2\pi i f t} x(t) dt \tag{1.2}$$

For a discrete time series voltage data $V(t)$ The power spectral density is defined as

$$P(\omega) = \sum_{-\infty}^{+\infty} r(k)e^{-j\omega k} \tag{1.3}$$

where r(k) is the autocorrelation function and is defined by $r(k) = E[y_t y_{t+k}]$ Inverse Fourier transform can be written as

$$r(k) = \frac{1}{2\pi} \int -\pi^{+\pi} P(\omega)e^{j\omega k} \tag{1.4}$$

$$r(k) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} P(w)e^{-j\omega k} \tag{1.5}$$

1.3 Types of noises

Noises can be classified on the basis of the power spectrum of the time series data

1.3.1 1/f noise

$1/f$ noise refers to the phenomenon of spectral density [1], $S(f)$ having the form

$$S(f) = constant/f^{\alpha} \tag{1.6}$$

where f is the frequency and α is the exponential factor. Depending on the value of α the noises can be classified. Detailed explanation about each type of noises are given below

1.3.1.1 White noise

This is the most common type of noise. White noise is just a random signal with a constant power spectral density. In white noise samples can be considered as sequence of uncorrelated random variables with zero mean and a finite variance. If the sample have normal distribution and zero mean then signal can be said as Gaussian white noise. Johnson-Nyquist noise [2] is approximately a white noise. Power spectral density of a white noise is usually zero throughout the frequency spectrum.In white noise value of α is almost equal to zero.

1.3.1.2 Pink Noise

Pink noise is an intermediate between the well understood white noise with no correlation in time and random walk (Brownian motion)[3] noise with no correlation between increments.Power spectrum of the pink noise yields a straight line with slope α between 0.4 to 1.6. power spectra are usually plotted in log-log plot. So

$$log(S(F)) = log(constant/f^{\alpha}) = -\alpha log(f) + log(constant) \tag{1.7}$$

From here it is clear that $-\alpha$ is the slope of the power spectrum. 1/f noise was discovered by Johnson(1925).Almost any resistor though which current is flowing exhibhits voltage fluctuations with a 1/f noise.

Chapter 2

Experimental design

The setup consist of a liquid nitrogen cryostat with temperature range from 77K-300K. The sample was placed to the sample holder using gold wires and silver-epoxy paste. Sample was connected in four probe geometry.

The circuit consist of two lock-in amplifiers. An AC current source is supplied to the sample via a load resistor. Voltage across the other two probes are passed through a low noise pre-amplifier. This amplifies the sample signal. The amplified signal is measured by Lock-In Amplifier. Voltage across the resistor is also measured by another Lock-In. The signal from the LocK-IN was transfered to the computer using GPIB interface.

2.1 Circuit Diagram

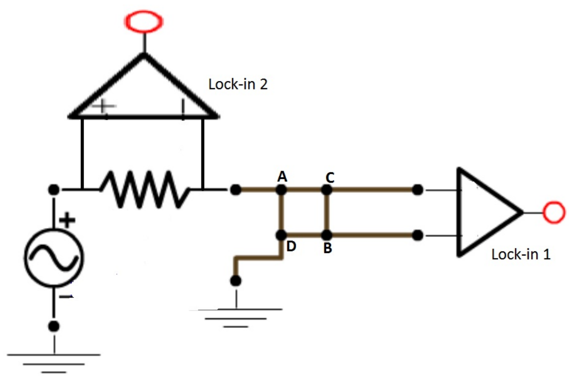

FIGURE 2.1

Temperature was kept constant using Temperature controller. Reference signal of frequency 31 Hz and amplitude 1.5 V was used from the Lock-In Amplifier. Voltage across the sample was measured using Lock-In Amplifier. The time series data from the cryostat was transferred to computer using a matlab code. Power spectrum of the data was calculated. The estimation of the power spectrum used a method. developed by Peter D. Welch using fast fourier transform and is known as the method of averaged periodogram" Process was repeated for different temperatures

Chapter 3

Result and Analysis

In this chapter we will look into the noise measurements data acquired and do some analysis. This will help us to understand more about the time series voltage data. Power spectrum of the sample is measured using two different algorithm . Histogram of the time series data is plotted. We will also have to figure out what properties of metal-insulator transitions can be deduced from the data.

3.1 Resistance-Temperature curve

We can find the resistance of a sample along a temperature domain by constant cooling and heating of the sample. Figure shows the resistance of V_2O_3 sample as a function of temperature range 80K to 220K. We choose this range because the metal-insulator transition is visible in this range.

The first order transition is visible at 150 K.

3.2 Noise measurements

Time series voltage data obtained from the sample can be analyzed to find various statistical informations like power spectral density and histogram. These information gives idea about the noise fluctuation in the sample

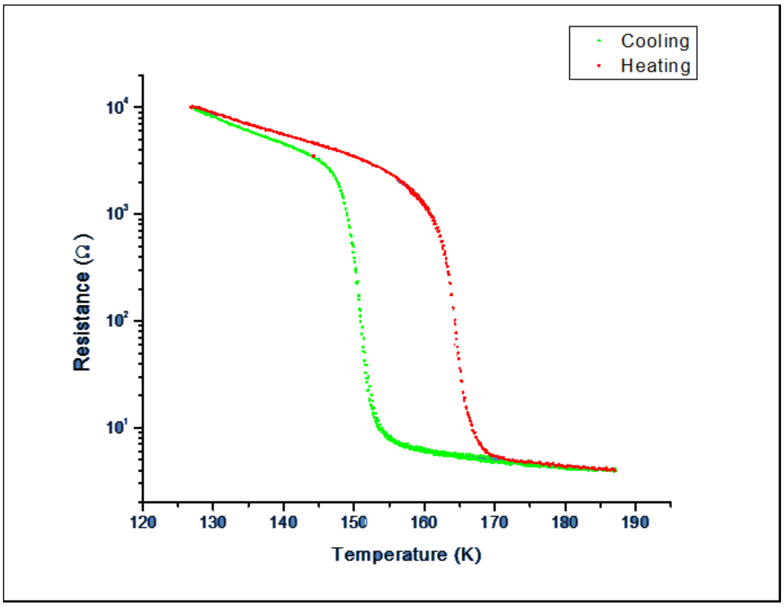

FIGURE 3.1: Resistance- Temperature curve

3.2.1 Time series data

Time series data gives us the idea about the magnitude of resistance fluctuations with temperature.The figure below shows the time series voltage data for a V_2O_3 sample while cooling.

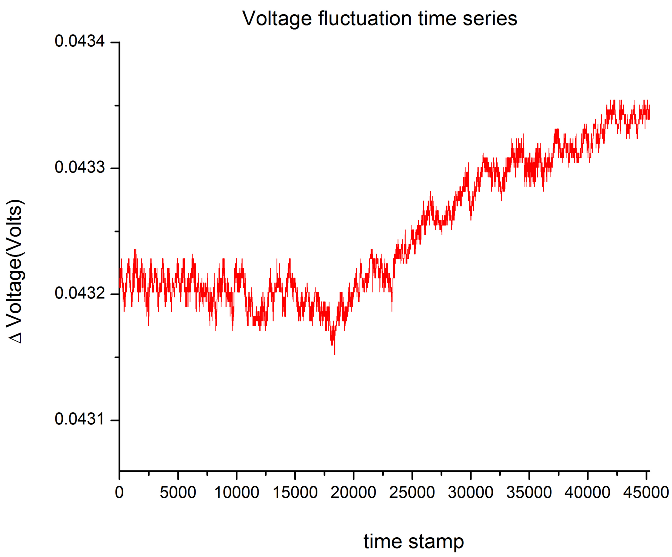

FIGURE 3.2: Times series data for 153 K

Since the metal-insulator transition is in between 150 K to 156 K , only that part is plotted. From the figure we can see that change in voltage from the mean voltage increases with decrease in temperature. This gives a basic idea about the amplitude of the noise.

3.2.2 Power Spectral density

As mentioned in earlier chapters power spectral density is a useful and reliable tool to identify time series fluctuations. It gives us the idea about pattern of noises in metal-insulator transition region. Figure 3.3 shows the power spectral density of the sample in a heating cycle with temperature varying from 160 K to 166K. This power spectrum was calculated using normal fourier transform algorithm.

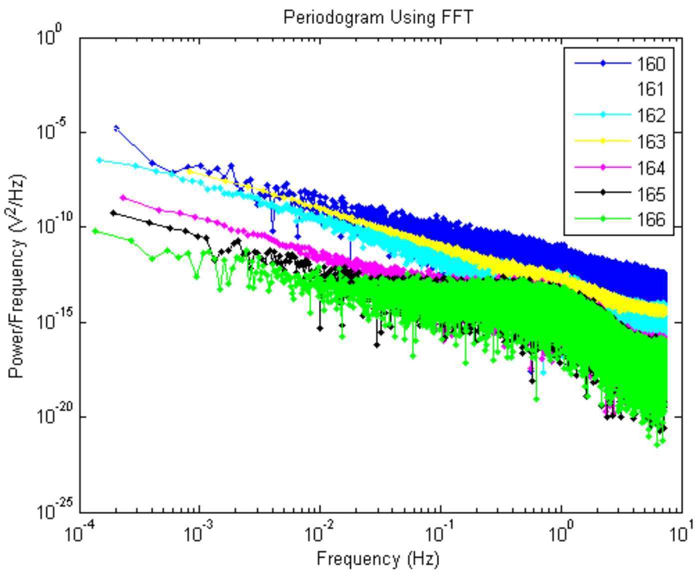

FIGURE 3.3: power spectrum for heating

From the below graph we can see clearly that the magnitude of the power spectrum decreases with temperature. Slope of the power spectral density varies with temperature.

Figure 3.5 shows us the power spectral density calculated using welch algorithm for periodogram. This smoothen the power spectrum.

In this figure we can clearly see the difference in noise with increase in temperature. There is a quick change in power spectrum from 160 K to 163 K.

In case of cooling the sample the results are almost similar with temperature range from 152 K to 156.5 K. Figure 3.6 shows the power spectral density of the

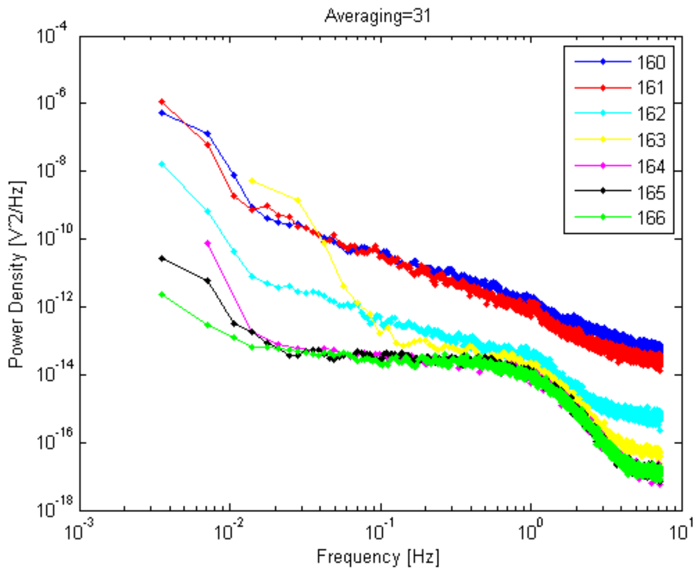

FIGURE 3.4: power spectrum for heating

sample using normal fourier transform algorithm. Here we can clearly identify the differences in slopes for different temperatures. Before 154 K the sample is in insulating phase and the slopes are pretty much different from the data after 154 K.

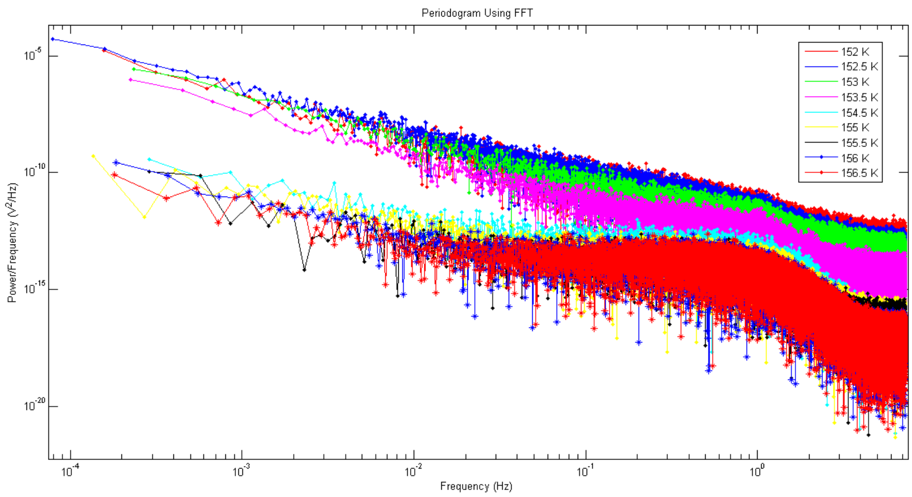

FIGURE 3.5: power spectrum for cooling

Figure 3.5 shows the power spectral density for cooling cycle using welch periodogram algorithm with averaging factor=31. Here also the pattern is similar.

Figure 3.7 shows the power spectrum using fourier transform algorithm for temperatures ranging from 127 K to 200 K. Here also we can see the same pattern.

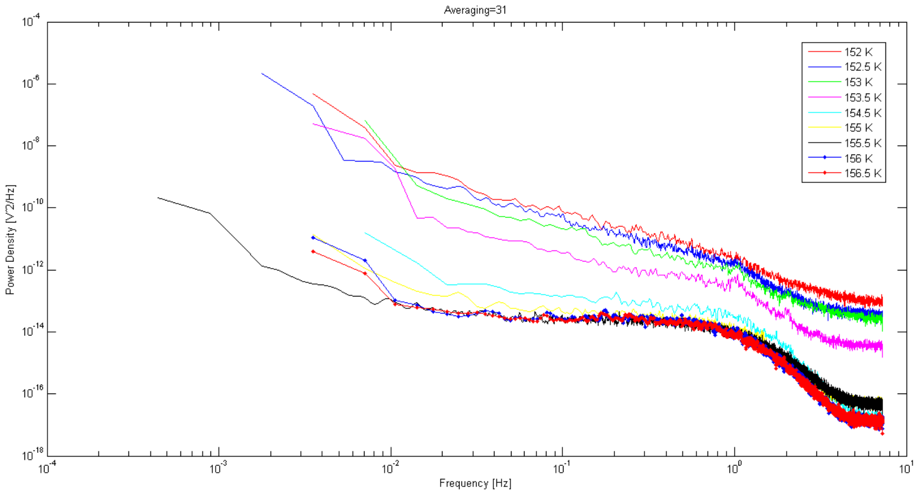

FIGURE 3.6: power spectrum for cooling

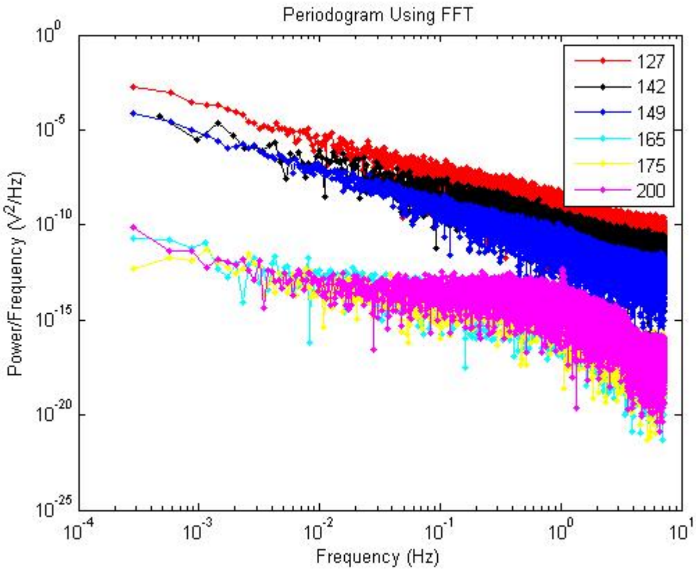

FIGURE 3.7: Power spectrum for temperature range

Figure 3.8 shows power spectrum using welch algorithm for temperature ranging from 127 to 200K

From the above data we can see that the power spectral density decreases with increase in temperature.

3.2.3 Slopes of Power spectral density

Slopes of the power spectral density can be calculated to find the type of noise. In insulating region conductance fluctuations behave similar to pink noise. For an

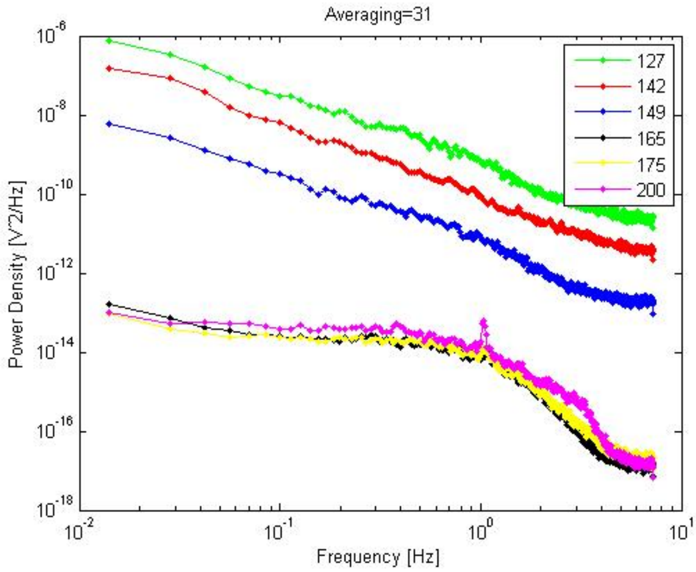

FIGURE 3.8

ideal pink noise slope parameter (α) should lie between -1.4 and -0.6.

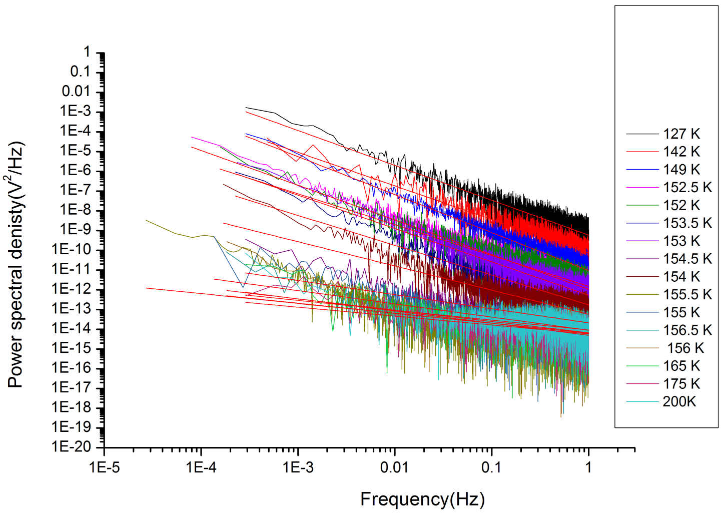

FIGURE 3.9: Power spectral density while cooling

From the above graph the slopes of power spectrum at each temperature was calculated for cooling using linear fit. The calculated slopes were plotted along with corresponding temperature.

From figure 4.9 slopes of the welch's periodogram was calculated using basic linear fit. In both cooling and heating the slope α was decreasing with increase in temperature. More clear analysis of the slopes can be seen by plotting the slope obtained against the corresponding temperature.

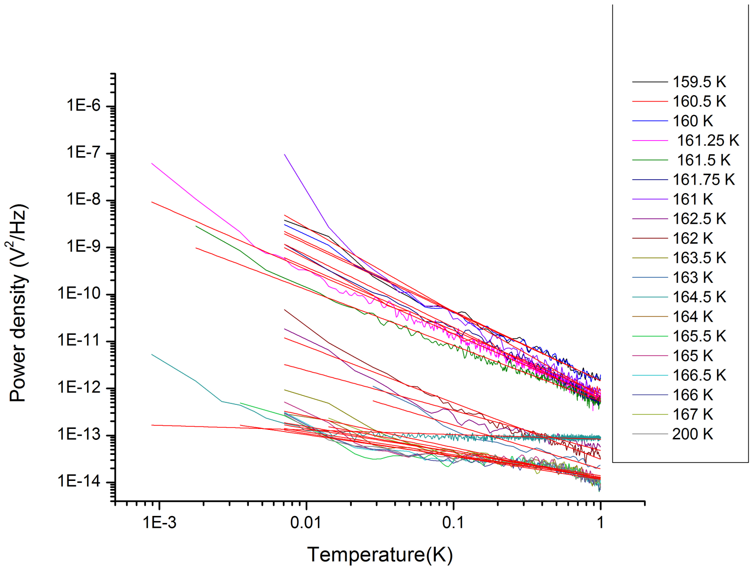

FIGURE 3.10: Power spectral density for heating

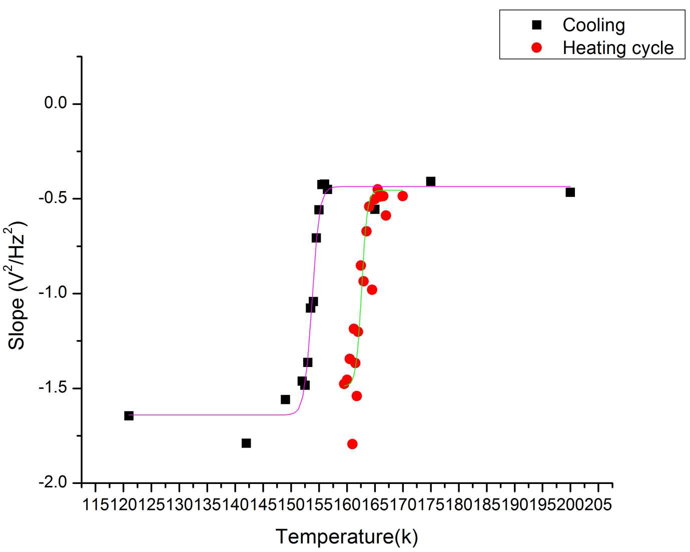

FIGURE 3.11: Slope vs Temperature

From the Slope vs Temperature graph we can clearly see that the power density slope for both heating and cooling is in between -0.5 to -1.5, $-0.5 < \alpha < -1.5$ which is close to the ideal range , $-0.6 < \alpha < -1.4$ for pink noise. The noise is said to be Brownian if the value of α is 2.In the insulating phase ($T < 155$ for cooling, $T < 165$ for cooling) the $1/f$ noise pattern show a pink noise dependence($\alpha < 1.6$). But in the conducting phase($T > 155$ for cooling, $T > 165$ for heating) the α value is in between 0 and -0.5 which can be considered as a white noise.

3.2.4 Gaussian nature of the noise

By calculating the basic histogram of the time series data we can find out the Gaussian nature of the data. Initially we plot the probability density of the time series of $\delta V/V^2$ for different temperature. The probability distribution should be normal for a gaussian dataset. Figure 3.12 shows the probability density of $\delta V/V^2$.

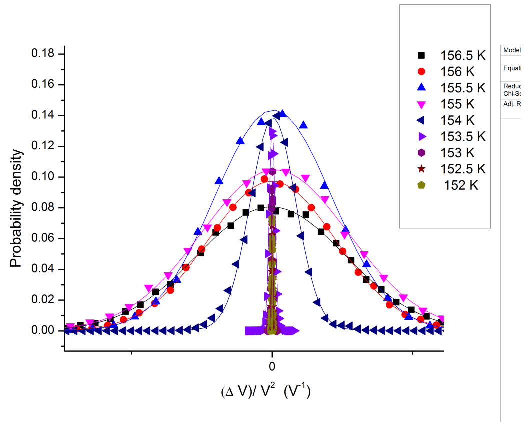

FIGURE 3.12: Probability density for different temperatures

The distribution is Gaussian for most of the temperatures in the dataset. There is a change in the FWHM and σ for the different temperatures. There is another way to plot the Gaussian nature by plotting ΔV^2 vs $ln(density)$. For an ideal Gaussian curve this plot should be linear.

In most temperatures this plot is linear. But there is a slight variation from the Gaussian at high values of ΔV

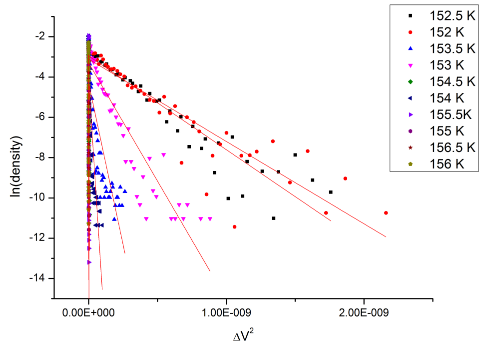

FIGURE 3.13: log of probability density)

Appendix A

Matlab code

```
clear all
close all
fina=[152,152.5,153,153.5,154,154.5,155,155.5,156,156.5];


for i=1:length(fina)
    name=strcat(num2str(fina(i)),'.txt');
    nameout=strcat(num2str(fina(i)),'-originwithout-a.txt');
    nameout1=strcat(num2str(fina(i)),'-originfftwithout-a.txt');

file = load (name);

fileID = fopen(nameout,'w');
fileID1=fopen(nameout1,'w');

x = file(:,2);
temp=file(:,1);
ui=size(x);
y=smooth(x,ui(1)/10);
meanr=mean(x);
delx=x-y;
delx1=x-mean(x);
%delx=delx./(x.^2);


Fs=14.5;
t(1)=0;
for i = 1:length(x)-1
    t(i+1) = t(i)+1/Fs;
end

N = length(delx1);
xdft = fft(delx1);
xdft = xdft(1:N/2+1);
psdx = (1/(Fs*N)) * abs(xdft).^2;
psdx(2:end-1) = 2*psdx(2:end-1);
freq = 0:Fs/length(delx1):Fs/2;
```

```
for i = 1:length(freq)
    if log10(freq(i))<0
fprintf(fileID1,'%.20f %.50f \r\n',freq(i),psdx(i));
    else
        psdx(i)=0;
    end



end




figure(2);

loglog(freq,psdx,'g.-');

title('Periodogram Using FFT')
xlabel('Frequency (Hz)')
ylabel('Power/Frequency (V^2/Hz)')
legend('127','142','149','165','175','200');
hold on;


figure(3);

nx = max(size(delx)); na = 55;
w = hanning(floor(nx/na));
[pxx,f] = pwelch(delx,w,0,[],Fs);

clear nx na w



for i = 1:length(f)
        if log10(f(i))<0
        fprintf(fileID,'%.20f %.50f \r\n',f(i),pxx(i));

        else
    pxx(i)=0;
        end
end

loglog(f,pxx,'.-');
title('Averaging=31')
xlabel('Frequency [Hz]');
ylabel('Power Density [V 2/Hz]');
legend('127','142','149','165','175','200');
hold on;
%}
```

```
end
```

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[1] b Aveek Bid Arindam Ghosh, a Swastik Kar and A. K. Raychaudhuric. A set-up for measurement of low frequency conductance fluctuation (noise) using digital signal processing techniques. *arxiv.org*, 72(12):4477–4479, February .

[2] M. B. WeIssrnan. 1/f noise and other slow, nonexponential kinetics in condensed matter. 62(1):1–20, January 1991.

[3] J. A Motchenbacher, C. D.; Connelly. Low-noise electronic system designr. *Wiley Interscience*, 69(3), March 1993.